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An Expanded Look into the Role of Economic Diversity on Unemployment

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Abstract: The empirical literature examining the relationship between economic diversity and economic growth and stability is inconclusive. Using fourteen years of data for all U.S. counties, this study re-examines the topic in hopes of gaining clarity. This study finds economic diversity to be negatively associated with increases in unemployment rates. This study also finds that counties with greater economic diversity experience larger absolute changes in unemployment rates after employment shocks in either direction. These results suggest that higher economic diversity promotes resilience but decreases stability.

1. Introduction

As noted by Wagner (2000), the empirical literature examining the relationship between economic diversity and economic growth and stability is inconclusive. Reasons for this include the variety of measures of diversity, geographic scales, and levels of industrial detail used in each study. With access to fourteen years of data for all U.S. counties, this study re-examines the topic in hopes of gaining clarity. This study finds that economic diversity, as measured by a normalized Shannon-Weaver entropy index using industrial employment, is negatively associated with changes in unemployment rates. This study also finds that counties with greater economic diversity experience larger absolute changes in unemployment rates after employment shocks in either direction. These results suggest that higher economic diversity promotes resilience but decreases stability.

1.1. IMPLAN's time series data

In 2016, IMPLAN Group completed the development of a time-series set of IMPLAN data spanning from 2001 to 2014. For this data set, the data for the years 2001-2012 were re-estimated using IMPLAN's latest methodologies, which have been honed over the past 20 years of data development, as well as revised and more current raw data. All years are based on the latest BEA Benchmark tables and IMPLAN's latest 536 sectoring scheme. This study uses the new data set to examine the relationship between economic diversity and unemployment levels and stability over time.

The primary purpose of re-estimating the 2001-2012 data was to produce a consistent data set that could be used for statistical analyses. Additional benefits include the following:

- 2005 IMPLAN data are available for the first time ever.
- This data series takes advantage of the improved raw data from many government data sources that are later revised after the annual IMPLAN data creation process.
- No projection of data was needed, since the data is all for past years.
- This is currently the only place in which IMPLAN's employment data are separated into wage and salary employment and proprietor employment.
- This data series uses consistent estimation methodologies that incorporate IMPLAN's best practices and improved data sources adopted throughout the years.
- This data series uses a consistent sectoring scheme – IMPLAN's current and most detailed.

1.2. The Shannon-Weaver Index of Economic Diversity

In order for an economy to withstand supply and demand shocks, it must either maintain its competitive advantage or have a sufficient variety of industries to reemploy displaced workers (Malizia and Ke, 1993). While economic specialization takes advantage of economies of scale (Skyes, 1950) and competitive advantage (Diamond and Simon, 1990), the performance of an area dominated by one sector is likely to be closely tied to the performance of that sector, which can become a liability for the area if the core industry suffers a national or regional downturn (Fitchen, 1995). Economic diversity is thought to enhance economic performance by: 1) shielding a region from the adverse effects of idiosyncratic external economic shocks; and 2) increasing the proportion of intermediate and final demand that can be supplied locally, thereby slowing the leakage of money out of the local economy.

Without denying the value of specialization and competitive advantage, the focus of this article is on economic diversity and one measure of economic diversity in particular: the Shannon-Weaver (S-W) Index. The S-W Index is an entropy method that measures the economic diversity of a region against a uniform distribution of employment across all industries. In other words, it is a measure of both the number of industries in a region and the extent to which the employment in that region is evenly distributed among those industries. It ranges in value from zero to one, with zero indicating minimum diversity and a value of one indicating maximum diversity. A value of zero (complete specialization) occurs when the economic activity of a region is concentrated in only one industry. A value of one (perfect diversity) occurs when all industries are present in the region, with employment spread equally among them.

The S-W Index has been calculated and displayed by the IMPLAN data and software system for economic impact analysis since their 1999 data set. In IMPLAN, the S-W Index for a region is calculated as follows:

$$\mathrm{S-W} = \frac{\sum_i^N \left(\frac{E_i}{E} * \log_2 \frac{E_i}{E}\right)}{\log_2 \frac{1}{N}} \quad (1)$$

where E_i is employment in industry i, E is total employment in the region, and N is the number of possible industries. Although equation (1) is written with logarithms of base 2 here, the base of the logarithm used when calculating the S-W Index can be chosen freely, though comparing S-W values across time or place requires that they are all calculated with the same log bases. Shannon and Weaver (1948) discuss logarithm bases 2, 10, and e, and these have since become the most popular bases in applications that use the S-W Index.

It should be noted that the S-W Index does not account for the fact that many of the industries in a region may be closely related and would therefore provide little protection were one of the other closely-related industries to suffer a major decline. For example, a given region would receive the same S-W Index if its 1,000 employees were spread in either of the two hypothetical patterns shown in Table 1. While both cases have 1,000 employees and five industries, with employment spread evenly amongst the five industries, it should be apparent that Case 1 represents a much more diverse economy than Case 2. This subtle difference between the two cases is not reflected in the S-W Index, which would give the same value to both cases. Wagner and Deller (1993) discuss this issue and propose an alternative measure of economic diversity.

Table 1. Two sample industry mixes resulting in the same S-W index values.

Case 1			**Case 2**	
Industry	**Employment**		**Industry**	**Employment**
Grain farming	250		Grain farming	0
Petroleum refining	250		Petroleum refining	0
Automobile manufacturing	0		Automobile manufacturing	250
Light truck and utility vehicle mfg	0		Light truck and utility vehicle mfg	250
Motor vehicle parts manufacturing	0		Motor vehicle body manufacturing	250
All other transportation equipment mfg	0		All other transportation equipment mfg	250
Wholesale trade	250		Wholesale trade	0
Legal services	250		Legal services	0

One might expect that aggregating closely-related sectors together, e.g., aggregating all the sectors in Case 2 in Table 1 in a single "Auto" industry, would improve the S-W Index by treating like sectors as a single sector, rather than as distinct sectors. Yet the S-W Index as currently calculated actually tends to increase when the employment data are aggregated into a smaller number of related sectors. This occurs for two reasons: when a region's employment data are aggregated into fewer sectors, there are fewer sectors with zero employment and the employment appears to be more evenly spread amongst those aggregated sectors, i.e., the aggregated sector smooths out the variation between the individual industries within the aggregated industry.

Related to this issue of sector aggregation is the issue of comparing S-W indices over time. Because the IMPLAN sectoring scheme changes periodically (in reflection of the BEA's Benchmark I-O tables, which are released roughly every five years), the number of sectors will change, which will influence the S-W Index calculation, rendering year-to-year comparisons imperfect when comparing across years with different sectoring schemes. One solution is to use the time series version of the IMPLAN data, which currently span from 2001 to 2014 and are all in the 536 sectoring scheme. This time series dataset also addresses the issue of consistency pointed out by the State of Hawaii's Department of Business, Economic Development and Tourism (2008).

While the S-W Index displayed in IMPLAN Pro and IMPLAN Online uses employment as the factor of choice, it is certainly possible to use other factors, such as employee compensation, as the factor of choice to give an alternate view and additional insight into the region's economic diversity. This could be useful if the industries in a given region vary widely in their levels of employee compensation, in which case even if employment were perfectly evenly spread amongst all industries, the employee compensation would not be.

The S-W Index should not be used in isolation to claim a particular region's overall economic health or prospects for future economic growth. An S-W Index is one of many possible measurements of diversity, and specialization can also be beneficial in some cases. Nonetheless, it can serve as a useful tool when considered alongside other metrics, both economic and non-economic.

In the case of bedroom community counties (i.e., counties in which most residents commute to another county to work), a relatively low S-W Index may represent less of a concern. For these counties it is the economic strength of the county in which its residents work which is of most importance (see the example of Lancaster County, PA, below).

Note that IMPLAN currently calculates the S-W Index based on total employment, which includes both wage and salary workers and proprietors. It may be instructive to investigate the S-W Index when just wage and salary employees are considered. This may be an important factor given that the proprietor data are residence based, while wage and salary employment data are place of work based[1].

The common critiques and alternative measurements of economic diversity are well-reviewed in Wagner (2000) and include, in brief, the following:

- Entropy-based measurements presume "an equal distribution of activities across sectors as the reference point for diversity" without any justification.
- Entropy-based measurements "do not account for any form of interindustry linkages," although they may serve as a proxy.
- Alternative proposals have included portfolio variance-based measurements and measurements extrapolated from inter-industry transaction tables ("A" matrices in the input-output literature).

Indeed, combining these alternative measurements of diversity and inter-industry relationships with more detailed and consistent longitudinal data could prove especially fruitful, though estimating empirical "A" matrices (that is, non-synthetic "A" matrices) would be especially difficult. This paper does not dispute the theoretical critiques of using the S-W Index as a predictor of economic growth or stability. Nevertheless, the goal of this study is to revisit the empirical findings of researchers who have used an entropy-based diversity measurement, like the S-W Index, to examine the relationship between industrial diversity and economic growth or stability.

[1] In the BEA's Regional Economic Accounts, income, depending on the type, can be recorded by place of production (where earned) or by place of residence (where received) (Bureau of Economic Analysis, 2015). BEA reports, "Estimates of wages and salaries, employer contributions for employee pension and insurance funds, and contributions for government social insurance (by employers and employees) are mainly based on source data that are reported by place of work (i.e., the county in which the employing establishment is located). In contrast, estimates of nonfarm proprietors' income and contributions for government social insurance by the self-employed are based on source data that are reported by the tax-filing address of the recipient. This address is often that of the proprietor's residence; therefore, these data are treated as if it were place of residence. Estimates of farm proprietors' income are based on data that are reported by the principal place of production. Because most farm proprietors live on, or near, their land, the place of production is treated as if it were the same as the place of residence."

2. Literature review

Using the Shannon entropy measure of economic diversity, Attaran (1984) found no statistically significant relationship between economic diversity and economic instability as measured by the standard deviation of unemployment but did find a statistically significant relationship between economic diversity and economic instability as measured by the standard deviation of *changes* in unemployment. However, major weaknesses of this analysis include a limited geographic scope (Oregon counties), a highly aggregate sectoring scheme (3-digit SIC), and the use of correlation coefficients, which do not account for numerous other factors that would be expected to influence the relationships.

The State of Hawaii Research and Economic Analysis Division (2008) found no significant relationships when regressing annual deviations of unemployment relative to its long-term trend on the annual estimates of diversity indexes. This study was also highly limited in its geographic scope, thereby limiting the wider application of its conclusions.

Also using an entropy measure of industrial diversity, Malizia and Ke (1993) found that more industrial diversity leads to lower unemployment rates and less employment instability in U.S. metropolitan areas. When employment shocks are excluded, the results below are consistent with Malizia and Ke's finding that economic diversity is associated with lower unemployment rates; however, when employment shocks are included, the results found here contradict their finding that diversity promotes stability. Methodologically, this study differs from the analysis by Malizia and Ke in several ways, most noteworthy among them being its temporal, geographical, and sectoral scope. In the analysis by Malizia and Ke, the dependent variables and several explanatory variables, including economic diversity, come from datasets with time intervals greater than one year. Although it has a larger geographic scope than many other previous studies, Malizia and Ke's study is limited to a specific type of geography, Metropolitan Statistical Areas (MSAs). It also uses a highly-aggregate sectoring scheme (two-digit SIC).

Deller and Watson (2016) use the 3-digit NAICS sectoring scheme and two different measures of economic diversity (the Herfindahl index and the log share index) to investigate the relationship between diversity and stability across four different metrics: unemployment rates, wages, establishments per capita, and the employment-to-population ratio. They measure stability with a variance-mean ratio of each of the four metrics. They find increased diversity to be positively associated with stability in the unemployment rate and with other metrics, except weekly wages. Deller and Watson use a spatial Durbin model which includes spatial lags of the dependent variable and independent variables as regressors. Since the research here uses positive and negative changes in the unemployment rate as the dependent variable, rather than unemployment rate stability, its results generally are not directly comparable to Deller and Watson's results. This paper's results do suggest, however, that diversity can exacerbate the adverse unemployment rate effects of a decline in total area employment (and may augment the beneficial unemployment rate effects of a rise in total area employment). This paper also uses variations on the spatial Durbin model as robustness checks.

3. Methods and data

The purpose of this study is to extend previous research to include a greater range of geographies and a greater number of time periods. This study examines the relationship between economic diversity, as measured by the Shannon-Weaver Index, and unemployment rate changes. This study builds upon and extends previous research efforts by including greater sector detail (531 sectors), geographic variability (3,130 counties[2]), a longer time period (2001-2014), and alternative statistical approaches.

4.1. Data

The data for all independent variables came from IMPLAN's time series data set, which currently spans from 2001 to 2014. IMPLAN's most prominent sources for employment and income data include the Bureau of Labor Statistics' (BLS) Quarterly Census

[2] For the sake of consistency, counties that did not exist in all 14 years or were changed during the times period were excluded from the analysis. These include Skagway-Angoon, AK, Hoonah-Angoon Census Division, AK, Skagway Borough, AK, Wrangell-Petersburg Census Area, AK, Petersburg Census Area, AK, Wrangell Borough, AK, Prince of Wales – Outer Ketchikan Census Area, AK, Prince of Wales-Hyder Census Area, AK, Boulder County, CO, Broomfield County, CO, Bedford City, VA, and Bedford County, VA.

of Employment and Wages (QCEW) data series and the Bureau of Economic Analysis' (BEA) Regional Economic Accounts (REA) data series.[3] The unemployment rate data, which served as the dependent variable in the present analyses, came from the Bureau of Labor Statistic's Local Area Unemployment Statistics (LAUS) series.

Although all of the data have an empirical basis, all are synthetic to some extent. LAUS data are based on the Current Population Survey, but ultimately they are model-based.[4] QCEW data may be the most empirical but have coverage gaps: QCEW does not include or systematically undercounts data for certain industries and is subject to non-disclosure rules. BEA REA data on employment and income are derived, in large part, from QCEW and IRS data and attempt to account for under-counting in QCEW data, but they also are subject to non-disclosure rules and are tabulated with a different classification scheme. IMPLAN constructs its data from all of these data series and uses additional data sources and inference methods to estimate data missing due to non-disclosure rules, which creates a more complete, albeit synthetic, dataset.

In accordance with the primary sources for IMPLAN employment data, IMPLAN employment data represent head-counts and therefore include a mix of part-time, full-time, and seasonal employment. In addition to wage and salary workers, IMPLAN employment also includes sole proprietors and partnerships; this is an important detail due to the fact that proprietor data are reported on a place-of-residence basis while wage and salary employment is reported on a place-of-work basis.

Table 2. Summary statistics.

Variable	Mean	Std. Dev.	Min.	Max	Skewness	Kurtosis
Area	1,122	3,695	1.80	153,687	27.81	1,025.52
TotalEmp	55,624	194,881	41.64	6,082,837	13.44	288.96
Population	96,448	311,684	42.00	10,100,000	14.75	364.85
NaturalAmenityScore	3.49	1.04	1.00	7.00	0.74	3.95
AvgPay	41,105	10,391	1,469	166,072	1.53	8.80
SWIndex	0.66	0.06	0.10	0.78	-1.41	7.18
URC	0.13	1.34	(9.60)	13.60	1.53	8.28
UR	6.59	2.80	1.10	29.10	1.21	5.28
MfgShare	0.15	0.07	-	0.68	1.35	7.01
AgShare	0.08	0.09	-	0.79	2.01	8.96
MiningShare	0.02	0.04	-	0.82	5.77	56.35
ConstructionShare	0.06	0.03	-	0.52	2.07	15.28
DurableShare	0.06	0.06	-	0.51	2.05	9.42

4.2. Statistical models

As the dependent variable, this study uses first differences in unemployment rates (unemployment rate change, abbreviated URC), as unemployment rate levels themselves had stationarity issues and did not fare as well in robustness checks of models. Additionally, first differences in unemployment rates lend themselves well to interpretations related both to stability and health. Small values, negative or positive, in URC imply stability, and negative values imply improvement.

Various types of models suitable to panel data were considered, including lagged dependent variable (LDV) models, fixed effects (FE) models, and random effects (RE) models. Ultimately, FE was favored over RE by an alternative to the Hausman test that does not require positive definiteness (Allison, 2009).[5] The model compares "within" (time-series effects) and "between" (cross-sectional effects) estimators in a hybrid RE model. Ultimately, the null hypothesis that the cross-sectional effects are equal to the time-

[3] See www.implan.com for more complete data source documentation.

[4] See http://www.bls.gov/lau/laumthd.htm.

[5] See here for more information about performing this test in Stata: http://www.stata.com/support/faqs/statistics/between-estimator/.

series effects was rejected. Therefore, a random effects (RE) model is rejected in favor of a fixed effects (FE) model. The LDV models tended to show similar results to the FE models, so discussion of both is included. Additionally, parameter estimates from LDV models and FE models can have a "bracketing" effect on the upper and lower bounds of the true population coefficient, assuming the model is properly specified (Angrist and Pischke, 2009).

The explanatory variable of most interest in this study is the S-W Index, lagged one year. Lagged employment shares in durable-goods manufacturing and mining, which previous researchers have considered unstable industries, are included to test the hypothesis that employment concentration in unstable industries contributes to higher unemployment. Lagged employment shares in agriculture and construction are also included due to their similarly volatile nature. An additional reason to include the shares of agricultural, mining, and construction employment is that these sectors tend to have higher levels of proprietor employment relative to other sectors. As noted previously, proprietor employment is residence based as opposed to place-of-work-based wage and salary employment. Proprietors are not excluded from the study because the LAUS data include them and because, for most proprietors, place of work and place of residence are the same.[6] Including these industry share of employment variables, however, has the shortcoming of changing the interpretation of the effects of the S-W Index. For example, if one were to control for all 2-digit NAICS[7] industry shares, the coefficient on the S-W Index (measured at higher industry resolution) would mean, roughly, the effect of a change in diversity within 2-digit NAICS industries with the relative sizes of those 2-digit shares and all other controls being equal. In the models used here, these industry shares improve model fit but do not substantially change the magnitude or sign of the coefficients on the S-W Index.

Malizia and Ke (1993) assert that social, environmental, and natural geographical factors can also affect metro-area unemployment rates systematically; however, their tests of different state and regional variables did not reveal any state-level variable that warranted inclusion in their final models. To account for regional differences, they divided the continental U.S. into eleven multi-state regions. While county-level natural amenity scores[8] from the USDA Economic Research Service were used in some model specifications, the FE model precludes the inclusion of time-invariant variables such as the natural amenity score. Furthermore, the natural amenity scores are available only for counties in the continental U.S., the use of which thus requires omitting Alaska and Hawaii.

Malizia and Ke (1993) propose population as an important control variable in estimating the diversity-stability relationship yet find it to be insignificant in both of their final models. To account for the wide variation in county area size across the U.S., the present study uses logs of population density and total employment. Malizia and Ke (1993) also included gender, race, and education variables in their final models; of these, only the female percentage of the labor force had a statistically significant (and negative) effect on unemployment and employment instability. Due to the difficulty in obtaining data on female labor force participation at the county level for 12 years, this was not tested in the present study. This study also tests for asymmetric effects of the S-W Index in the event of positive and negative employment shocks by using various specifications of the employment shock (dummy variables for different signs and levels of employment change and continuous variables of employment change as a percentage of total employment), interacted with the S-W Index.

4. Data analysis

This study finds a significant and persistent relationship between economic diversity and unemployment rate changes. A significant relationship persists with and without the inclusion of employment shares in various "unstable" industries, and with and without the inclusion of interaction terms to allow for asymmetric effects of employment growth and decline. However, the nature of this relationship appears to be dynamic, its direction depending on whether the local economy is currently experiencing employment growth or decline.

When interaction variables combining the size and sign of an employment shock with lagged S-W Index are excluded, FE models do not show a significant effect of economic diversity on URC; however, the LDV model shows a significant and negative (i.e.,

[6] LAUS specifically includes self-employed people, agricultural workers, and private household workers.
[7] North American Industry Classification System

[8] The natural amenities scale is a measure of the physical characteristics of a county that enhance the location as a place to live. The scale combines six measures of climate, topography, and water area that reflect environmental qualities most people prefer.

beneficial) effect on URC, as long theorized but inconclusively tested.[9] These results are reported in the first two columns of Table 4. The model fit statistics reported in Table 4 suggest that the FE model outperforms the LDV model by a narrow margin. From a theoretical standpoint, however, the LDV model better represents unemployment rate dynamics. That is, given the covariates, future variation in unemployment rates is more related to past changes in unemployment rates than it is to unobserved, time-invariant features of individual counties.

When interaction terms are included to allow for asymmetry in the effect of economic diversity interacted with employment shock sign and level on URC, a consistent pattern emerged that seems to suggest that economic diversity has a destabilizing effect in either direction; that is to say, in cases of negative employment changes a larger S-W Index exacerbated the increase in unemployment rate, whereas in cases of positive employment changes a larger S-W index boosted the decline in unemployment rate. Stated differently, negative employment shocks have a more severe effect on unemployment rates when there is greater economic diversity. The same dynamic appears with positive employment shocks, albeit with smaller and less significant coefficients. This destabilizing effect, whereby a higher S-W Index exacerbates the effect of employment shocks, occurs in both the FE and LDV versions of the model and accords with the notion that a more diverse economy tends to contain and magnify local shocks. The destabilizing effect of high diversity in the midst of a negative employment shock also emerged in spatial regression models, whereas the directly beneficial effect of a high S-W Index lost its significance.

The average marginal effect of S-W Index, when measured at the average values of employment shocks, is still negative and significant in LDV models with employment shock interactions, but it is no longer significant in corresponding FE models. Again, the FE models here show slightly better fit statistics, but the LDV models are preferred for theoretical reasons. The models with the employment shock interactions outperform the models without employment shock interactions. Figure 1 shows the average marginal effects (computed with Stata's margins command) of positive and negative employment growth as shares of an area's total employment at different levels of S-W Index, with shaded confidence intervals.

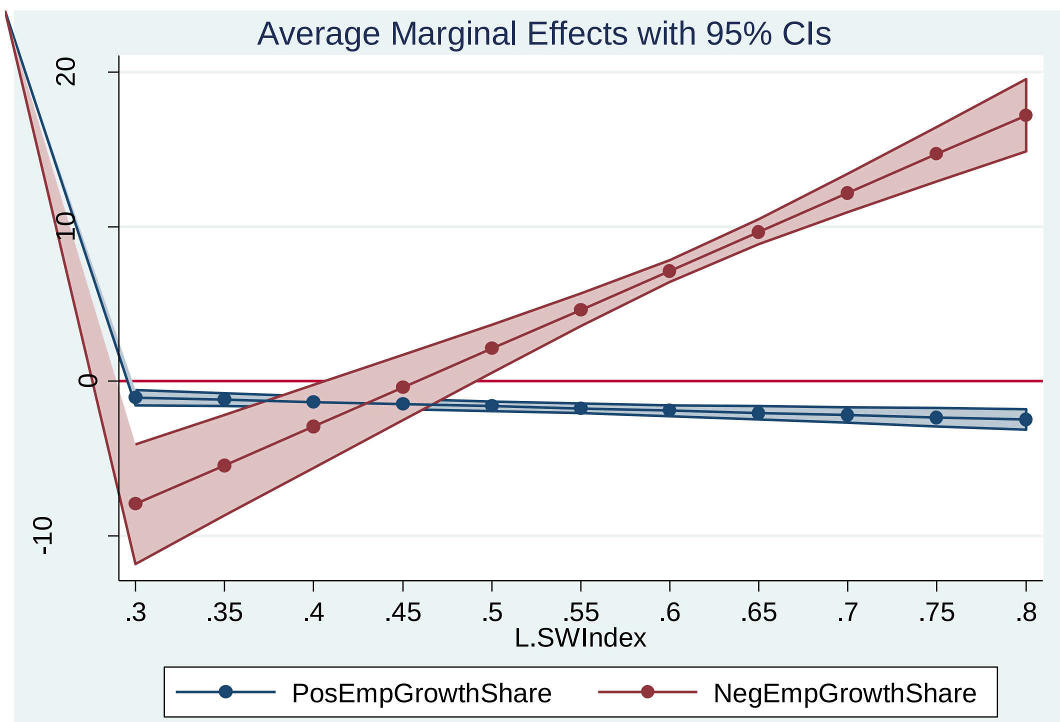

Figure 1. Average marginal effects of employment shocks as share of total employment.

[9] To avoid confusion, "negative" and "positive" are used solely in terms of numerical sign, rather than as synonyms for "adverse" and "beneficial", respectively.

Table 3 reports the average marginal effects of employment shocks from a similar model, in which employment shocks were represented by categorical variables and interacted with a 1-period lag of S-W Index.[10] These effects correspond to the "FE – Segmented Shocks" model in Table 4. The variable names indicate the employment shock range as a share of total employment. For example, NegGrowth01to025 means that there was a negative employment shock between 1% and 2.5% of the area's total employment. As the table shows, the bigger shock, the bigger the effect on URC in the expected direction. All results are significant, except negative shocks greater than 20% of an area's employment.

Table 3. Average marginal effects.

	dy/dx	Std. Error	z	P>|z|
1.NegGrowth01to025	0.050693	0.014491	3.5	0.000
1.NegGrowth025to05	0.242605	0.017543	13.83	0.000
1.NegGrowth05to1	0.734524	0.032274	22.76	0.000
1.NegGrowth1to2	1.193585	0.128333	9.3	0.000
1.NegGrowth2Plus	0.319163	0.465125	0.69	0.493
1.PosGrowth01to025	-0.08966	0.012599	-7.12	0.000
1.PosGrowth025to05	-0.18031	0.013329	-13.53	0.000
1.PosGrowth05to1	-0.23097	0.017934	-12.88	0.000
1.PosGrowth1to2	-0.25481	0.042968	-5.93	0.000
1.PosGrowth2Plus	-0.40558	0.168179	-2.41	0.016

Figures 2 and 3 plot the effects of these variables at different levels of S-W Index. The exacerbating effect of higher levels of S-W Index shows more prominently in the event of negative employment shocks. Confidence intervals were omitted from the charts to improve readability, but it should be noted that none of the intervals in Figure 2 include zero at 0.65 and above on the x-axis, except for NegGrowth2Plus. Most are significant at even more positions; see the appendix for the tabular output used in Figures 2 and 3.

This finding goes against some of the expectations reflected in the literature but appears to be fairly robust. The rest of the variables in the models perform as expected, insofar as (increasing) employment gains are good (better) for unemployment rates and (increasing) employment losses are bad (worse). Again, this result is consistent between FE and LDV specifications.[11] The results remain much the same when quadratic transformations of S-W Index are included and interacted with employment shocks, but increasing values of S-W Index below 0.45 do tend to show a stabilizing effect in the event of a negative employment shock.[12] Thus, this model is plausible and consistent across a variety of specifications. The destabilizing effect of S-W-based diversity may be due to the higher level of interdependence between sectors in regions with higher economic diversity. In such regions, more inputs (goods and services) are presumably available locally for other local industries to purchase, in which case the shrinking of one industry may be more likely to cause contractions in other industries through reductions in such input purchases. Likewise, a growing industry in such a region may have a greater influence on the growth of other local industries through such input purchases. If so, this should be thought of as a re-characterization of the "shielding" theory: more than just protecting an economy from negative external shocks, higher levels of diversity shield an economy from external shocks in either direction (i.e., whether positive or negative) while magnifying the effects of internal shocks due to the more self-contained nature of the economy.

It should also be noted that when employment change levels were used in place of percentages, the emergent pattern seemed to suggest that economic diversity has a greater effect on protecting economies' URC from large employment losses than it does

[10] The model specification is largely the same as in Table 3, except that only a 1-period lag of S-W Index is included.

[11] They are also consistent when more than one lag of the dependent variable is included.

[12] Very few counties have such low values of S-W Index, and the confidence intervals include 0.

on generating large increases in employment. This is in line with the findings of Goetz et al. (2016), who, using a similar but simpler measure of economic diversity, found that counties with greater diversity succeeded in warding off a severe recession, but diversity did not contribute to a resumption of growth. However, taking the log of the employment growth levels as an alternative way to normalize their distribution yielded similar results as when using percentage employment growth; that is, economic diversity was found to exacerbate unemployment rate changes in both directions. Such a transformation (percentages or logs) is preferred to the use of levels, since percentages indicate the magnitude of an employment shock relative to the size of the economy, thereby providing a greater level of confidence in the conclusions that result from the use of these transformations.

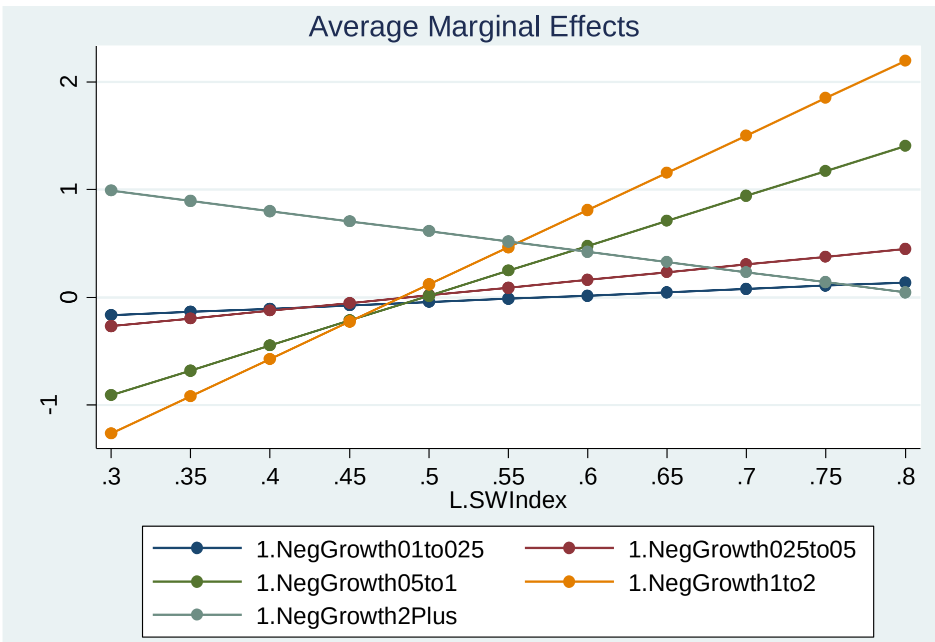

Figure 2. Average marginal effects of negative employment growth share indicators.

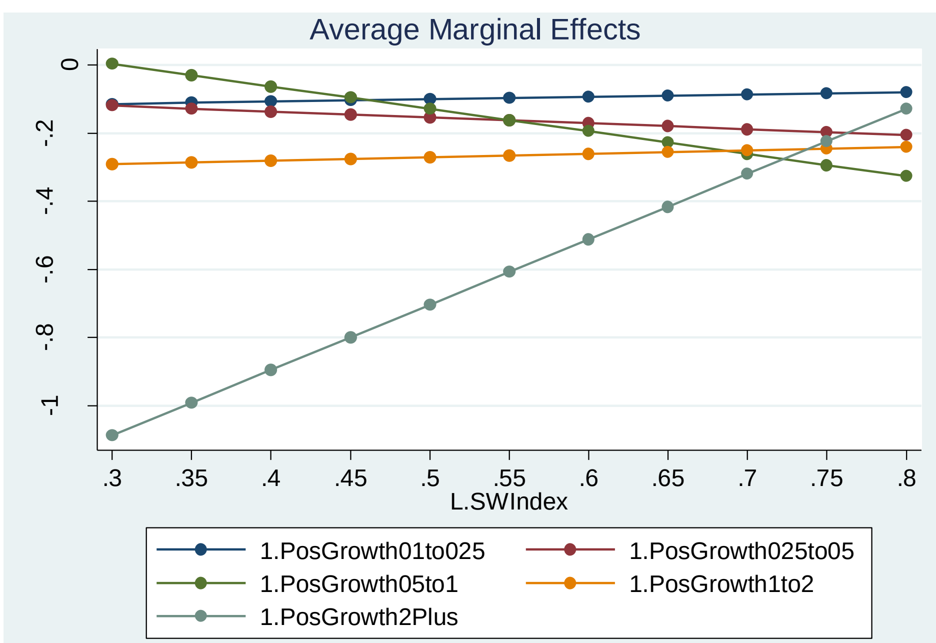

Figure 3. Average marginal effects of positive employment growth share indicators.

The covariates show noteworthy results as well. In line with theory and in contrast to the findings of Malizia and Ke (1993), who found the concentration of employment in durable-goods manufacturing to have no perceptible influence on changes in unemployment rates, this study found that durable-goods manufacturing has a consistently significant and positive effect on URC. The same results were found for construction. The share of employment in mining was usually negative, though of a smaller magnitude and in times of lesser significance. This could be a function of the rapidly evolving energy sectors during the time period under study. The influence of the share of employment in agricultural sectors on URC was negative when significant; however, this variable was only significant when the interaction terms were not included. Employment in this sector is more seasonal in nature compared to any of the other included sectors. Therefore, any sweeping conclusions about this particular explanatory variable cannot be drawn from this study. Table 4 compares coefficient values and model fit statistics across a variety of preferred models, including those with interaction terms of S-W Index and employment shocks. Coefficients for those interactions are excluded from Table 4 to improve readability but are included in the appendix. Average earnings usually has a positive and significant effect on URC, which may be due to increased labor force participation as average earnings rise combined with decreased demand for labor as its price rises.[13]

Although this study has not resolved questions of the direction of causality between unemployment and economic diversity, several tests suggest that causality is in the expected direction. The first table in the appendix summarizes a basic lagged FE model, a basic LDV model with a one-period lag of S-W Index, and other specifications of both types of models with different lead and lag structures of the variable of interest, S-W Index. Such models were tested in the interest of determining causality, with the expectation that past values of S-W Index would significantly affect URC and that future values would not. The results largely confirm that expectation, but some interesting patterns are observed. In the LDV models, a 1-period lag of S-W Index is always significant and always negative. Leads of S-W Index almost always are not significant. These results are consistent when "unstable" industry shares are included as controls and whether just a 1-period lag of URC or both 1- and 2-period lags of URC are included in the model. Contemporaneous values of S-W Index, however, always have a positive sign and are always significant; such inconsistency raises the concern that a 1-period lag may not be the appropriate model structure. S-W Index is highly correlated from year to year, but the change in S-W Index from year to year has a significant negative correlation. URC, which is already in terms of year-over-year changes, has a positive correlation with the prior year's value, but a negative correlation with its value from 2 years prior; accordingly, if there's a relationship between S-W Index and URC, the signs for a 1-period lag and contemporaneous term will tend to differ. Indeed, when multiple leads and lags are included, the signs tend to alternate. Similar results occur in corresponding FE models. Although this could indicate an endogeneity problem, it is more likely an artifact of independent trends in S-W Index and URC.[14] In an attempt to resolve these effects in an LDV model, both a 1-period lag of S-W Index and the contemporaneous value of S-W Index were interacted with a 1-period lag of URC, yielding more consistent results. In this model, the average marginal effects of both the 1-period lag and contemporaneous values had the same sign, and both were significant, but the magnitude of the effect of the 1-period lag was much greater (-3.1 versus -0.7), supporting the use of a 1-period lag of S-W Index. It was not possible perform an analogous test with the FE models. Overall, such results are consistent with, although certainly not decidedly in favor of, a causal relationship between S-W Index and URC.

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[13] In a model that estimated the cross-sectional effects of average pay, the opposite result was observed – higher average pay had a negative effect on URC.

[14] For another specification check, an interaction term between an identity variable and time was added to allow entity-specific time trends. All signs and significance levels remained the same. The only noticeable change between the 1-period lag FE model and the model with the entity-trend terms is that the size of the coefficient on the log of population density increased from 1.7 to 5.7. Pooled OLS models were also estimated using S-W Index as the dependent variable, with a 1-period lag of URC and the sum of several recent periods' URCs as independent variables, with the expectation that 1-period lag of the dependent variable would have no explanatory power independently from the summed URCs. This was true in a variety of specifications and is consistent with a dataset in which S-W Index and URC are associated, but changes in recent URC, relative to S-W Index, do not affect S-W Index. See Vaisey and Miles (2014) for a motivating discussion.

Table 4. Preferred models.

Variable	FE – 1 lag	LDV – 1 lag	LDV – Segmented Shocks	LDV - Cont. Shocks	FE – Cont. Shocks	FE – Segmented Shocks
L.SWIndex	0.616	-0.848***	included with employment shock interactions			
	-0.539	-0.095				
L.LnAvgPay	0.346***	0.0926***	0.119***	0.119***	0.431***	0.437***
	(0.0525)	(0.0152)	(0.0162)	(0.0163)	(0.0505)	(0.0512)
L.LnTotalEmp	1.715***	0.00741	0.0358***	0.0353***	0.900***	0.901***
	(0.106)	(0.00427)	(0.00459)	(0.00479)	(0.0912)	(0.0921)
L.LnPopDensity	-0.0541	0.0125***	0.00790*	0.00760*	0.183	0.197
	(0.122)	(0.00305)	(0.00335)	(0.00333)	(0.112)	(0.111)
L.DurableShare	4.076***	0.539***	0.186***	0.165**	3.746***	3.872***
	(0.387)	(0.0593)	(0.0521)	(0.0519)	(0.384)	(0.370)
L.AgShare	0.0777	-0.299***	-0.236***	-0.228***	0.127	-0.0179
	(0.380)	(0.0440)	(0.0478)	(0.0457)	(0.354)	(0.357)
L.MiningShare	-0.00235	-0.164*	-0.0401	-0.0371	0.774	0.780
	(0.502)	(0.0818)	(0.0793)	(0.0855)	(0.467)	(0.427)
L.ConstructionShare	4.031***	1.705***	2.166***	2.046***	4.153***	4.418***
	(0.627)	(0.146)	(0.178)	(0.190)	(0.710)	(0.602)
L.URC		0.0489***	0.0179**	0.0182**		
		(0.00658)	(0.00644)	(0.00647)		
Continuous Employment Shocks	no	no	no	yes	yes	no
Categorical Employment Shocks	no	no	yes	no	no	yes
N	40,695	40,688	40,688	40,688	40,695	40,695
AIC	99,730	101,558	99,158	99,269	97,861	97,685
BIC	99,902	101,748	99,520	99,492	98,068	98,029
F	1,106	1,117	650	1,003	1,034	665
"Adjusted" or "within" R^2	0.64	0.62	0.64	0.64	0.65	0.65

*Standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001.*
All models include year as a factor variable and are estimated with robust standard errors clustered around an identity variable.

Using panel data on counties raises the concern of spatial autocorrelation, which is the cross-sectional analogue to autocorrelation over time. This paper tested errors using Moran's I statistic in the LDV specifications, as well as Pesaran's (2004) test of cross sectional independence, which is a general test of cross-sectional independence that does not depend on a pre-specified spatial weights matrix.[15] Both suggested the presence of spatial autocorrelation. In accordance with the advice given in LeSage (2014), this paper estimated both a spatial Durbin error model and a spatially-lagged regressors model for both the FE and LDV specifications. The spatially-lagged regressors model uses spatial lags of only the independent variables. The spatial Durbin error model adds to the spatially-lagged regressors model by specifying a

[15] A spatial weights matrix is used in spatial regression models to set the structure and level of spatial connections. For example, in a matrix with rows *i* and columns *j* one would put a value in place (*i*, *j*) that represents the distance from *i* to *j*, perhaps 1 if they share a border and 0 otherwise.

spatial lag in the error term. For the spatial specifications, this study used a spatial weighting matrix based on inter-county commuting patterns. The spatial Durbin error model specification led to several reductions in coefficient values and losses of significance, but the finding that in cases of negative employment changes a larger S-W Index exacerbated the increase in unemployment rate persisted across all of these specifications and maintained statistical significance. Additionally, the "indirect" effects of negative employment shocks – that is, decreases in total employment in neighboring counties – further substantiate the interpretation of diversity as creating a "shield." As expected, negative employment shocks in neighboring counties lead to increases in the home county's unemployment rate, but if that neighboring county's diversity is higher the effect of the negative employment shock on the home county is attenuated. In other words, diversity exacerbates the within-county effect of a negative employment shock while attenuating the inter-county effects of a negative employment shock.

5. Conclusions and suggestions for further research

This study has found a significant and persistent relationship between economic diversity and unemployment. However, the nature of this relationship appears to be dynamic, its direction depending on whether the local economy is currently experiencing employment growth or decline. In addition, the results vary depending on whether employment change level is used in place of percent employment change when allowing for asymmetry. The finding that higher diversity is destabilizing – that is, that it leads to larger increases in URC in the event of a negative employment shock – is this paper's most robust finding.

While the statistical significance of the S-W Index effect on URC is noteworthy, the magnitude of the coefficient tends not to exceed three in any of the specifications. Practically speaking, this is small. Across all counties and all years in the sample, the annual change in S-W Index ranges from -0.22 to 0.23, with a mean of 0.0006 and a standard deviation of 0.009; refer to Figure 4 for a histogram. For example, with a coefficient of -3, even a large change in S-W Index as rare as 0.05 implies only a -0.15 unit change in URC, all else equal. So, in a county that will move from 6% to 5% unemployment rate (URC of -1) not including the S-W Index effect, the 0.05 increase in S-W Index will change that to a 6% to 4.85% (URC of -1.15) decline. Such a change certainly would matter for unemployed workers at the margin but may not justify a policy shift.

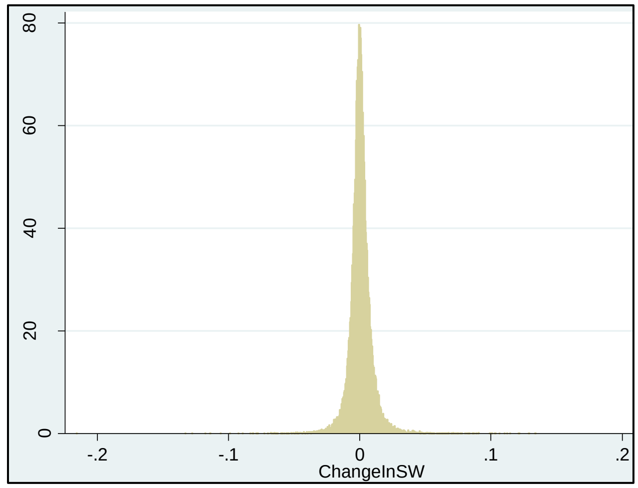

Figure 4. Histogram of level changes in S-W Index.

In light of these results and the availability of this new data set, further research is unquestionably warranted. Interesting extensions would be to exclude proprietor employment and/or to use employment hours as opposed to employment counts. While there is potential benefit to conducting the analysis at a different geographic level, e.g., MSAs, or examining metropolitan counties separately from non-metropolitan counties, it is important to note that the results of Deller and Watson (2016) were stable across both rural and urban areas. Conducting the analysis at the 3-digit NAICS level would make it more comparable to Deller and Watson (2016) and thus may be conducive to identifying the reasons behind the divergent conclusions. Including more time periods would also likely help strengthen and clarify the findings.

References

Allison, P. 2009. *Fixed Effects Regression Models*. Los Angeles: Sage.

Angrist, J., and J-S. Pischke. 2009. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, NJ: Princeton University Press.

Attaran, M. 1984. The relation of economic diversity to levels, growth rates, and stability of unemployment and income. Dissertations and Theses Paper 542, Portland State University. pdxscholar.library.pdx.edu/cgi/viewcontent.cgi?article=1541&context=open_access_etds.

Bureau of Economic Analysis. 2015. Local Area Personal Income Methodology. www.bea.gov/regional/pdf/lapi2014.pdf, pp. I-3 – I-4, accessed October 17, 2016.

Deller, S., and P. Watson, 2016. Did regional economic diversity influence the effects of the Great Recession? *Economic Inquiry* 54(4): 1824-1838.

Diamond, C.A., and C.J. Simon. 1990. Industrial specialization and the returns to labor. *Journal of Labor Economics* 8(2): 175-201.

Fitchen, J.M. 1995. Why rural poverty is growing worse: Similar causes in diverse settings. In E.N. Castle (ed.) *The Changing American Countryside*. Lawrence, KS: University Press of Kansas.

Goetz, S.J., Fleming, D.A., and Y. Han. What makes one economy more resilient than another? *The Conversation*, March 7, 2016. theconversation.com/what-makes-one-economy-more-resilient-than-another-54374?utm_source=newswire&utm_medium=email&utm_term=397138_HTML&utm_content=03-15-2016-09-25&utm_campaign=alumni%20newswire.

Kort, J.R. 1981. Regional economic instability and industrial diversification in the U.S., *Land Economics* 57: 596-608.

Lesage, James L. 2014. What regional scientists need to know about spatial econometrics. *Review of Regional Studies* 44(1): 13-32.

Ljungqvist, A., and M. Smolyansky. 2016. To cut or not to cut? On the impact of corporate taxes on employment and income. *Finance and Economics Discussion Series* 2016-006, Washington, DC: Board of Governors of the Federal Reserve System. dx.doi.org/10.17016/FEDS.2016.006.

Malizia, E.E., and S. Ke. 1993. The influence of economic diversity on unemployment and stability. *Journal of Regional Science* 33(2): 221-35.

Pesaran, M.H. 2004. General Diagnostic Tests for Cross Section Dependence in Panels. IZA Discussion Paper Series, 1240.

Rozin, P., and E.B. Royzman. 2001. Negativity bias, negativity dominance, and contagion. *Personality and Social Psychology Review* 5(4): 296–320.

Shannon, C. E. 1948. A mathematical theory of communication. *The Bell System Technical Journal* 27: 623–656.

Skyes, J. 1950. Diversification of industry. *The Economic Journal* 60(240): 697-714.

State of Hawaii Research and Economic Analysis Division. 2008. Measuring Economic Diversification in Hawaii. Department of Business, Economic Development and Tourism. files.hawaii.gov/dbedt/economic/data_reports/EconDiversification/Economic_Diversification_Report_Final%203-7-08.pdf.

Vaisey, S., and A. Miles. 2014. What You Can—and Can't—Do with Three-Wave Panel Data. Sociological Methods and Research. stephenvaisey.com/documents/threewavepanel.pdf.

Wagner, J.E. 2000. Regional Economic Diversity: Action, Concept, or State of Confusion. *Journal of Regional Analysis and Policy* 30: 1-22.

Wagner, J.E., and S.C. Deller. 1993. A Measure of Economic Diversity: An Input-Output Approach. USDA Forest Service and the University of Wisconsin-Extension. www.aae.wisc.edu/cced/937.pdf.

Wagner, J.E., and S.C. Deller. 1998. Measuring the effects of economic diversity on growth and stability. *Land Economics* 74(4): 541-556.

Appendix

Table A1. Models with Multiple Leads and Lags.

Variable	FE - 1 lag	LDV - 1 lag	FE - 1 lag, contemp.	LDV - 1 lag, contemp.	FE - 3 leads, 3 lags	LDV - 3 leads, 3 lags
SWIndex			3.378***	2.612***	4.002***	3.798***
			(0.709)	(0.660)	(0.990)	(0.969)
L.SWIndex	0.616	-0.848***	-1.447	-3.368***	-0.750	-3.591***
	(0.539)	(0.0950)	(0.750)	(0.660)	(1.066)	(1.006)
L2.SWIndex					0.965	0.123
					(0.961)	(0.908)
L3.SWIndex					-3.050**	-1.897*
					(0.945)	(0.844)
F.SWIndex					-1.152	-0.797
					(0.881)	(0.831)
F2.SWIndex					1.506	1.945*
					(0.963)	(0.947)
F3.SWIndex					-1.641	-1.111
					(0.952)	(0.768)
L.URC		0.0489***		0.0492***		0.0216**
		(0.00658)		(0.00659)		(0.00755)
L.LnAvgPay	0.346***	0.0926***	0.346***	0.100***	-0.697***	-0.282***
	(0.0525)	(0.0152)	(0.0527)	(0.0152)	(0.138)	(0.0323)
L.LnTotalEmp	1.715***	0.00741	1.743***	0.00475	2.290***	0.0167
	(0.106)	(0.00427)	(0.104)	(0.00418)	(0.168)	(0.00873)
L.LnPopDensity	-0.0541	0.0125***	-0.0386	0.0125***	0.646**	0.0344***
	(0.122)	(0.00305)	(0.122)	(0.00303)	(0.231)	(0.00540)
L.DurableShare	4.076***	0.539***	4.045***	0.518***	6.045***	0.958***
	(0.387)	(0.0593)	(0.386)	(0.0582)	(0.649)	(0.104)
L.AgShare	0.0777	-0.299***	0.177	-0.310***	-1.157	-1.169***
	(0.380)	(0.0440)	(0.378)	(0.0440)	(0.606)	(0.0836)
L.MiningShare	-0.00235	-0.164*	-0.0124	-0.158*	-0.0330	-0.790***
	(0.502)	(0.0818)	(0.484)	(0.0802)	(0.781)	(0.126)
L.ConstructionShare	4.031***	1.705***	4.027***	1.706***	1.921*	1.580***
	(0.627)	(0.146)	(0.631)	(0.146)	(0.918)	(0.219)
N	40,695	40,688	40,695	40,688	25,035	25,028
AIC	99,730	101,558	99,685	101,526	65,005	67,302
BIC	99,902	101,748	99,866	101,724	65,175	67,489
F	1,106	1,117	1,058	1,065	834	880
"adjusted" or "within" r2	0.64	0.62	0.64	0.62	0.65	0.63

*Standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001. All models include year as a factor variable and are estimated with robust standard errors clustered around an identity variable.*

Table A2. Output for Figures 2 and 3.

```
Average marginal effects                        Number of obs     =     40,695
Model VCE    : Robust

Expression   : Linear prediction, predict()
dy/dx w.r.t. : 1.NegGrowth01to025 1.NegGrowth025to05 1.NegGrowth05to1 1.NegGrowth1to2 1.NegGrowth2Plus
1.PosGrowth01to025 1.PosGrowth025to05 1.PosGrowth05to1 1.PosGrowth1to2 1.PosGrowth2Plus
1._at        : L.SWIndex       =          .3
2._at        : L.SWIndex       =         .35
3._at        : L.SWIndex       =          .4
4._at        : L.SWIndex       =         .45
5._at        : L.SWIndex       =          .5
6._at        : L.SWIndex       =         .55
7._at        : L.SWIndex       =          .6
8._at        : L.SWIndex       =         .65
9._at        : L.SWIndex       =          .7
10._at       : L.SWIndex       =         .75
11._at       : L.SWIndex       =          .8
------------------------------------------------------------------------------------
                    |            Delta-method
                    |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------------+---------------------------------------------------------------
1.NegGrowth01to025  |
                _at |
                  1 |  -.1655982   .0965633    -1.71   0.086    -.3548588    .0236625
                  2 |  -.1351676   .0838613    -1.61   0.107    -.2995328    .0291976
                  3 |   -.104737   .0712147    -1.47   0.141    -.2443152    .0348412
                  4 |  -.0743064   .0586588    -1.27   0.205    -.1892755    .0406627
                  5 |  -.0438758   .0462678    -0.95   0.343    -.1345591    .0468074
                  6 |  -.0134453   .0342214    -0.39   0.694     -.080518    .0536275
                  7 |   .0169853   .0230659     0.74   0.461     -.028223    .0621936
                  8 |   .0474159   .0149499     3.17   0.002     .0181146    .0767172
                  9 |   .0778465   .0156685     4.97   0.000     .0471369    .1085561
                 10 |   .1082771   .0244548     4.43   0.000     .0603465    .1562076
                 11 |   .1387077   .0357926     3.88   0.000     .0685555    .2088598
-------------------+----------------------------------------------------------------
1.NegGrowth025to05  |
                _at |
                  1 |   -.266735   .1068341    -2.50   0.013    -.4761259    -.057344
                  2 |  -.1950747   .0921696    -2.12   0.034    -.3757238   -.0144256
                  3 |  -.1234144   .0775944    -1.59   0.112    -.2754967    .0286679
                  4 |  -.0517541   .0631707    -0.82   0.413    -.1755664    .0720582
                  5 |   .0199062    .049032     0.41   0.685    -.0761947    .1160071
                  6 |   .0915665   .0355203     2.58   0.010      .021948     .161185
                  7 |   .1632268   .0237321     6.88   0.000     .1167128    .2097408
                  8 |   .2348871   .0175697    13.37   0.000     .2004512     .269323
                  9 |   .3065474   .0223189    13.73   0.000     .2628031    .3502917
                 10 |   .3782077   .0336384    11.24   0.000     .3122778    .4441377
                 11 |    .449868    .046999     9.57   0.000     .3577517    .5419843
-------------------+----------------------------------------------------------------
1.NegGrowth05to1 at |
                  1 |  -.9088675   .1489907    -6.10   0.000    -1.200884   -.6168512
                  2 |  -.6776548   .1270774    -5.33   0.000    -.9267219   -.4285877
                  3 |  -.4464421    .105382    -4.24   0.000     -.652987   -.2398971
                  4 |  -.2152294   .0840735    -2.56   0.010    -.3800103   -.0504484
                  5 |   .0159834    .063542     0.25   0.801    -.1085567    .1405234
                  6 |   .2471961   .0448675     5.51   0.000     .1592574    .3351347
                  7 |   .4784088   .0315414    15.17   0.000     .4165888    .5402288
                  8 |   .7096215   .0313511    22.63   0.000     .6481744    .7710686
                  9 |   .9408342   .0444656    21.16   0.000     .8536831    1.027985
                 10 |   1.172047   .0630695    18.58   0.000     1.048433    1.295661
                 11 |    1.40326   .0835738    16.79   0.000     1.239458    1.567061
-------------------+----------------------------------------------------------------
1.NegGrowth1to2  at |
                  1 |  -1.262408   .2930097    -4.31   0.000    -1.836696   -.6881195
                  2 |  -.9168684   .2409404    -3.81   0.000    -1.389103   -.4446339
                  3 |  -.5713289   .1901507    -3.00   0.003    -.9440175   -.1986403
                  4 |  -.2257893   .1420203    -1.59   0.112    -.5041439    .0525652
                  5 |   .1197502   .1004471     1.19   0.233    -.0771226    .3166229
                  6 |   .4652897   .0769216     6.05   0.000     .3145262    .6160533
                  7 |   .8108293   .0874738     9.27   0.000     .6393838    .9822747
                  8 |   1.156369   .1236682     9.35   0.000     .9139836    1.398754
                  9 |   1.501908   .1698335     8.84   0.000     1.169041    1.834776
                 10 |   1.847448   .2197736     8.41   0.000       1.4167    2.278196
                 11 |   2.192987   .2714127     8.08   0.000     1.661028    2.724947
-------------------+----------------------------------------------------------------
```

1.NegGrowth2Plus _at						
1	.9885709	.9269481	1.07	0.286	-.8282141	2.805356
2	.8943903	.7517391	1.19	0.234	-.5789913	2.367772
3	.8002097	.5811056	1.38	0.168	-.3387363	1.939156
4	.7060291	.420653	1.68	0.093	-.1184356	1.530494
5	.6118485	.2879365	2.12	0.034	.0475034	1.176194
6	.5176679	.2357098	2.20	0.028	.0556852	.9796506
7	.4234873	.308065	1.37	0.169	-.180309	1.027284
8	.3293067	.4482658	0.73	0.463	-.5492781	1.207891
9	.2351261	.6112885	0.38	0.701	-.9629773	1.433229
10	.1409455	.7830059	0.18	0.857	-1.393718	1.675609
11	.0467649	.9587577	0.05	0.961	-1.832366	1.925895
1.PosGrowth01to025 _at						
1	-.1141293	.0847371	-1.35	0.178	-.280211	.0519523
2	-.1106861	.0738231	-1.50	0.134	-.2553767	.0340046
3	-.1072428	.0629484	-1.70	0.088	-.2306195	.0161339
4	-.1037995	.0521377	-1.99	0.046	-.2059875	-.0016116
5	-.1003563	.0414409	-2.42	0.015	-.181579	-.0191336
6	-.096913	.0309765	-3.13	0.002	-.1576258	-.0362002
7	-.0934697	.021093	-4.43	0.000	-.1348113	-.0521281
8	-.0900265	.0131708	-6.84	0.000	-.1158407	-.0642122
9	-.0865832	.01205	-7.19	0.000	-.1102008	-.0629656
10	-.0831399	.0189767	-4.38	0.000	-.1203337	-.0459462
11	-.0796967	.0286044	-2.79	0.005	-.1357602	-.0236331
1.PosGrowth025to05 _at						
1	-.1189389	.1065492	-1.12	0.264	-.3277716	.0898938
2	-.1275733	.0925287	-1.38	0.168	-.3089262	.0537797
3	-.1362077	.0785461	-1.73	0.083	-.2901551	.0177398
4	-.144842	.064627	-2.24	0.025	-.2715086	-.0181755
5	-.1534764	.050822	-3.02	0.003	-.2530858	-.0538671
6	-.1621108	.0372596	-4.35	0.000	-.2351383	-.0890832
7	-.1707452	.0243482	-7.01	0.000	-.2184667	-.1230236
8	-.1793795	.014019	-12.80	0.000	-.2068563	-.1519028
9	-.1880139	.0141202	-13.32	0.000	-.215689	-.1603389
10	-.1966483	.0245229	-8.02	0.000	-.2447124	-.1485842
11	-.2052827	.0374502	-5.48	0.000	-.2786837	-.1318816
1.PosGrowth05to1 _at						
1	.003521	.1006964	0.03	0.972	-.1938402	.2008823
2	-.02947	.0870361	-0.34	0.735	-.2000577	.1411176
3	-.0624611	.0734727	-0.85	0.395	-.206465	.0815427
4	-.0954522	.0600717	-1.59	0.112	-.2131906	.0222862
5	-.1284433	.0469723	-2.73	0.006	-.2205074	-.0363793
6	-.1614344	.0345202	-4.68	0.000	-.2290927	-.0937761
7	-.1944255	.0237549	-8.18	0.000	-.2409842	-.1478668
8	-.2274166	.0180103	-12.63	0.000	-.2627162	-.192117
9	-.2604077	.0217227	-11.99	0.000	-.3029834	-.2178321
10	-.2933988	.0317301	-9.25	0.000	-.3555887	-.2312089
11	-.3263899	.0439221	-7.43	0.000	-.4124757	-.2403041
1.PosGrowth1to2 _at						
1	-.2911609	.2060533	-1.41	0.158	-.695018	.1126962
2	-.2860468	.1757858	-1.63	0.104	-.6305807	.058487
3	-.2809327	.1457971	-1.93	0.054	-.5666899	.0048244
4	-.2758186	.1163035	-2.37	0.018	-.5037692	-.047868
5	-.2707045	.0878048	-3.08	0.002	-.4427988	-.0986102
6	-.2655904	.061696	-4.30	0.000	-.3865123	-.1446685
7	-.2604763	.0426217	-6.11	0.000	-.3440132	-.1769394
8	-.2553622	.0417173	-6.12	0.000	-.3371266	-.1735978
9	-.2502481	.0598128	-4.18	0.000	-.3674789	-.1330173
10	-.245134	.0856055	-2.86	0.004	-.4129178	-.0773502
11	-.2400199	.113985	-2.11	0.035	-.4634263	-.0166135
1.PosGrowth2Plus _at						
1	-1.087438	.3366747	-3.23	0.001	-1.747308	-.427568
2	-.9915066	.2787899	-3.56	0.000	-1.537925	-.4450885
3	-.895575	.2232592	-4.01	0.000	-1.333155	-.4579949
4	-.7996433	.1723731	-4.64	0.000	-1.137488	-.4617982
5	-.7037117	.1316329	-5.35	0.000	-.9617074	-.445716
6	-.60778	.1126449	-5.40	0.000	-.8285599	-.3870001
7	-.5118484	.1256879	-4.07	0.000	-.7581921	-.2655047
8	-.4159168	.1632572	-2.55	0.011	-.7358951	-.0959384
9	-.3199851	.212733	-1.50	0.133	-.7369342	.096964
10	-.2240535	.2675905	-0.84	0.402	-.7485213	.3004143
11	-.1281218	.3251169	-0.39	0.694	-.7653392	.5090955

Note: dy/dx for factor levels is the discrete change from the base level.

Table A3. Interaction Coefficients for Employment Shock – S-W Index Interaction Models.

	LDV - Segmented Shocks	LDV - Cont. Shocks	FE - Cont. Shocks	FE - Segmented Shocks
L.SWIndex	-1.278*** (0.172)	-1.249*** (0.141)	-0.158 (0.568)	-0.311 (0.528)
L.LnAvgPay	0.119*** (0.0162)	0.119*** (0.0163)	0.431*** (0.0505)	0.437*** (0.0512)
L.LnTotalEmp	0.0358*** (0.00459)	0.0353*** (0.00479)	0.900*** (0.0912)	0.901*** (0.0921)
L.LnPopDensity	0.00790* (0.00335)	0.00760* (0.00333)	0.183 (0.112)	0.197 (0.111)
L.DurableShare	0.186*** (0.0521)	0.165** (0.0519)	3.746*** (0.384)	3.872*** (0.370)
L.AgShare	-0.236*** (0.0478)	-0.228*** (0.0457)	0.127 (0.354)	-0.0179 (0.357)
L.MiningShare	-0.0401 (0.0793)	-0.0371 (0.0855)	0.774 (0.467)	0.780 (0.427)
L.ConstructionShare	2.166*** (0.178)	2.046*** (0.190)	4.153*** (0.710)	4.418*** (0.602)
L.UnempChangeFromPreviousYear	0.0179** (0.00644)	0.0182** (0.00647)		
1.NegGrowth01to025	-0.326* (0.163)			-0.367* (0.175)
1.NegGrowth01to025#cL.SWIndex	0.570* (0.243)			0.618* (0.260)
1.NegGrowth025to05	-0.649*** (0.189)			-0.727*** (0.196)
1.NegGrowth025to05#cL.SWIndex	1.336*** (0.287)			1.441*** (0.298)
1.NegGrowth05to1	-2.118*** (0.256)			-2.377*** (0.281)
1.NegGrowth05to1#cL.SWIndex	4.262*** (0.407)			4.671*** (0.447)
1.NegGrowth1to2	-3.177*** (0.531)			-3.431*** (0.624)
1.NegGrowth1to2#cL.SWIndex	6.547*** (0.947)			6.889*** (1.101)
1.NegGrowth2Plus	0.342 (1.620)			0.808 (1.913)
1.NegGrowth2Plus#cL.SWIndex	0.285 (2.965)			-1.108 (3.495)
1.PosGrowth01to025	-0.0893 (0.141)			-0.116 (0.150)
1.PosGrowth01to025#cL.SWIndex	0.00848 (0.206)			0.0593 (0.219)
1.PosGrowth025to05	-0.0452 (0.173)			-0.0466 (0.192)
1.PosGrowth025to05#cL.SWIndex	-0.179 (0.256)			-0.166 (0.283)
1.PosGrowth05to1	0.251 (0.174)			0.226 (0.186)
1.PosGrowth05to1#cL.SWIndex	-0.702** (0.263)			-0.625* (0.282)
1.PosGrowth1to2	-0.0301 (0.350)			-0.261 (0.402)
1.PosGrowth1to2#cL.SWIndex	-0.281 (0.557)			0.154 (0.637)
1.PosGrowth2Plus	-1.577* (0.636)			-1.389 (0.739)
1.PosGrowth2Plus#cL.SWIndex	2.118 (1.136)			1.830 (1.313)
NegEmpGrowthShare		-21.86*** (3.094)	-24.84*** (3.733)	
cL.SWIndex#c.NegEmpGrowthShare		47.48*** (5.031)	51.74*** (6.056)	
PosEmpGrowthShare		1.076 (0.554)	0.0721 (0.524)	
cL.SWIndex#c.PosEmpGrowthShare		-4.103*** (1.020)	-2.082* (1.014)	